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MEASURING THE EFFECTS OF LEAN MANUFACTURING SYSTEMS ON FINANCIAL ACCOUNTING METRICS USING DATA ENVELOPMENT ANALYSIS

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Abstract

Just-in-Time (JIT) manufacturing, also known as Lean Manufacturing, provides a strategy by which firms may improve their financial performance. Which indicators, in the form of conventional ratios derived from a firm's financial statements, are truly made more favorable as a result of lean manufacturing systems is well documented. However, the use of conventional financial ratios, as input into parametric test procedures intended to highlight changes in manufacturing performance, may limit the extent of the analysis, and assumes the ratios are constructed from multivariate normal distributions. This study examines the effect of lean manufacturing implementation on the financial performance of 18 different firms using a technique referred to as data envelopment analysis (DEA). DEA is a linear programming technique that allows assessment of the efficiency of an operating unit, and may be a useful alternative to conventional ratio analysis due to its affording simultaneous examination of multiple inputs and outputs. The analyses include significance testing of DEA performance rating changes as a result of lean manufacturing implementation, a comparison of the implications of the DEA output to that of corresponding financial ratios, and tests for normality of the parameters studied.

Key words: Data Envelopment Analysis; DEA; Just-in-time; JIT; Lean Manufacturing.
JEL classification: M11.

Introduction

Since the 1970's, the just-in-time (JIT) philosophy, also referred to as lean manufacturing, has been utilized in manufacturing to varying degrees and with mixed financial results. Successful implementation of JIT is expected to lead to lower inventory carrying costs, increased utilization of operational assets, increased responsiveness to customer needs, and improved product quality. Inconclusive assessments, among similar firms, of the financial benefits of lean systems may result from the dispersion of the degree to which JIT has been adopted, from that of simple inventory reduction to incorporation of the entire lean manufacturing philosophy and infrastructure. Sakakibara et al. (1997) determined that JIT practices have less of an impact on a firm's performance than the infrastructure needed to achieve the lower levels of work-in-process (WIP) inventory. Taiichi Ohno, the executive who streamlined Toyota's process, considered JIT and the supporting infrastructure to be a single lean system, defining waste as anything that does not contribute to the value of the customers' product, including costly inventory. When identifying value, one must consider the entire fulfillment process, including the problem-solving function, from design through engineering to launch; information management, from order-taking through detailed scheduling to delivery; and the physical transformation task, converting raw materials to a finished product in the hands of the customer (Womack and Jones, 1996). Thus, lean systems confined to mere inventory reduction may fail, for example, due to the inability of the supply base to respond, the lack of a quality function sufficient to impart corrective action obviated by decreased inventory levels, or the lack of a structured maintenance program to ensure machine uptime once covered by inventory buffers.

In addition to the varied degree to which lean manufacturing practices have been implemented, the corporate efficiency improvements and subsequent financial gains resulting from lean

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systems, as measured by conventional financial accounting ratios, may be clouded by the limitations of the ratios themselves. These ratios are normally expressed as some output per unit of input, such that the output may be adjusted for the size of the firm. However, the outputs, or numerators, may not exhibit proportionality over the range of the inputs (denominators) used. Furthermore, many financial ratios are related in such a way that an improvement in one ratio comes at the expense of another. Finally, the comparison of financial ratios often involves the use of parameters that erroneously assume multivariate normality.

This paper is intended to examine the effect of lean systems on the performance of 18 companies from 7 different three-digit SIC codes, using information from the firms' financial statements during the period from 1989 to 1998. During the given time period, the study focuses on the lean systems implementation year, referred to as the adoption year, the two years preceding the adoption year, and three years post-adoption. Specifically, the characteristics of the distributions of the firms' financial ratios, such as the return on assets (ROA), asset turnover (ATO), inventory turnover (ITO), labor utilization (LUT) and the cash return on assets (CROA), are evaluated, and trends in the operational performance as indicated by the ratios, resulting from lean implementation, are assessed. Additionally, the financial inputs and outputs that comprise these ratios were studied using a non-parametric technique referred to as data envelopment analysis (DEA). DEA generates an efficient frontier composed of linear combinations of the inputs and outputs of each decision-making unit (DMU) being studied. DMUs not found on this efficient frontier are deemed relatively inefficient, and the magnitude of the slack encountered in the subsequent sensitivity analysis provides insight into the resources that are being inefficiently consumed (Charnes et al., 1978). Thus, DEA, as applied to financial statement analysis, provides a scalar measure of overall financial performance while using multiple input and output variables, allowing simultaneous assessment of many ratios (Charnes and Cooper, 1985). This study highlights differences in the DEA efficiency measures over the period studied to determine the statistical significance of improvements in operational efficiency resulting from JIT adoption. A review of the literature containing various evaluations of lean systems using conventional ratios is presented, followed by overviews of ratio analyses and DEA. The specific techniques employed in this study are then described, followed by a presentation of the results and conclusions.

The Effect of JIT on Firm Performance: Previous Research

JIT production methods generally lead to greater operational flexibility, improved quality, and lead time reductions. Because JIT and lean manufacturing systems focus on allowing the customer to "pull" material through the process, only replenishing inventories upon receipt of an order, the impact of such systems should be manifest in the inventory and asset turnover metrics. If the reduction in assets and improved efficiency reduces overall costs, then there should be a subsequent increase in the firm's return on assets. As resources are freed by the elimination of non-value-added activities, productivity is expected to rise, as should labor utilization. It is reasonable to expect that reductions in accounts receivable and inventory, along with increases in productivity, will also positively impact cash flow from operations, making the firm a more efficient converter of resources to cash. Great is the volume of studies that have been performed to assess the effect of lean systems on the financial health and productivity of various industries, and varied are both the analytical approaches taken and the results obtained.

Balakrishnan et al. (1996), testing the significance of changes in median ROA, for pre-adoption vs. post-adoption JIT and non-treatment control firms, found that the ROA actually decreased after inventory management systems were implemented, as did the ROA of control firms. Testing the magnitude of the ROA decrease for treatment versus non-treatment firms yielded no significant differences. However, the ROA decrease was significantly less for firms with non-concentrated customer bases, i.e., those not required to pass on JIT-related savings to their customers. Furthermore, firms that showed higher depreciation-to-cost ratios upon lean implementation, indicating a larger investment in JIT, did not exhibit a significant dilution of the savings from lean manufacturing adoption by the higher committed costs.

Kinney and Wempe (2002) re-examined the effect of JIT adoption on operational and financial performance, using a larger sample size than Balakrishnan et al. (1996). They found that adopters of lean systems produced increases in inventory turnover (ITO) that were six to eight times greater than their non-adopting counterparts, with a corresponding decrease in inventory-to-total-assets. The ROA response for JIT adopters improved, on average, more than non-adopters, and no significant difference in ROA was found between firms of varying customer base concentration. They explored the ROA response further by assessing the effect of lean implementation on both the profit margin and asset turnover (ATO) measures. The data revealed a stronger association between increases in profit margin and ROA, indicating that the removal of non-value-added costs is a greater boon than the mere increase in asset turns due to inventory reductions.

Sakakibara et al. (1997) defined JIT infrastructure practices as the activities that provide support for the use of JIT practices, such as employee involvement, design for manufacturability, mistake-proofing, work force development, proper organization, production pull, and quality management. Using canonical correlation analysis, focusing on the degree of statistical significance and the magnitude of the correlation coefficient, they set out to determine the interrelationship of JIT practices, infrastructure practices, manufacturing performance and competitive advantage. While no significant relationship between JIT practices and manufacturing performance was found, the relationship between lean infrastructure and JIT practices was strong. Furthermore, manufacturing performance was highly dependent on the combined effect of JIT practices and supporting infrastructure, and resulted in a statistically significant competitive advantage. It was concluded that JIT practices and the associated inventory reductions have value only when they drive the establishment of the necessary lean manufacturing infrastructure.

The focus of lean manufacturing systems on eliminating all but real-value-added activities should lead to reduced costs and, hence, increased productivity. Defining productivity as value added per employee, or the firm's sales less the costs of purchased materials and labor divided by the total number of employees, Lieberman and Demeester (1999) evaluated the correlation between work-in-process (WIP) inventory reduction and productivity changes. Using data from 52 Japanese automotive companies, strong negative correlations were found linking productivity and the WIP/sales ratio. For a heterogeneous group of automotive parts suppliers, fixed-effect regression models, allowing for firm-specific WIP factors, revealed that the WIP/sales ratio exhibited a significant effect on productivity, with the model coefficient implying that a 10% reduction in WIP brought about nearly a 1% increase in productivity. Subsequent Granger causality tests were in keeping with the 10-to-1 relationship, with productivity increases lagging inventory reductions by about one year. The causality models also deemed capital investment per worker as significantly improving productivity, with the investment becoming effective in one to two years. The coefficients indicated that a 10% increase in capital per worker led to an average increase of 2% in labor productivity.

Boyd et al. (2002) used regression to establish the significance of trends in financial metrics resulting from JIT implementation for 31 companies from a variety of manufacturing industries. They found the most significant changes, both statistically and in magnitude, to occur in the inventory turnover and labor utilization ratios. It was concluded that, while efficient transfer of WIP inventory to the cost of goods sold may result from inventory reduction efforts alone, the improved labor utilization can result only from a more pervasive deployment of lean manufacturing practices. Their work did not show a translation of operational improvement to a significant change in net income, however, although a positive net income trend was exhibited.

Conventional Ratio Analyses

Because of the uniform contents of financial statements, financial analysis using conventional accounting ratios is common practice. By normalizing a specific financial output to some input, one may compare specific indicators of performance to some industry standard, as well as allow for the comparison of firms of different size. Multivariate statistical methods using ratios are often employed to make decisions regarding financial performance, assuming normality and constant returns to scale. However, there may be problems with the underlying assumptions. Fernandez-Castro and Smith (1994) highlighted four problems with the nature of financial ratios. First, when comparing firms using ratios, one assumes strict proportionality between the numerator and denominator. If they are related in any other way, such as by an intercept term, an interaction term, or in a nonlinear fashion, a simple ratio cannot supply all the information embodied in the two variables. However, in the case of ROA, for example, it is clear that, regardless of the proportionality, a high value is preferable to a low value. Second, because of the proliferation of an unlimited number of ratios from corporate financial statements, there is the problem of choosing which ratios to examine in a given analysis. Predictive studies that incorporate an excess of ratios into the analyses may produce information that is redundant or difficult to interpret, while normative use requires the choice of ratios applicable to the targets upon which policy is based. Therefore, the choice of ratios as univariate indicators of performance often neglects consideration of possible conflicts or interdependencies between the metrics chosen, furthering the difficulties of both the omission of variables and the creation of unmanageable redundant information. Third, financial ratios, especially when used in normative applications, are not considered in aggregate form, and combining them for predictive purposes requires assessment of their relative contributions to the prediction. Furthermore, although regression-based techniques can be used to generate predictive information, the statistical assumptions underlying the regression approach are often violated. Most often, the assumption of multivariate normality is overlooked, and in the case of non-proportionality, the distribution will be skewed. Taking such assumptions into consideration in order to generate an acceptable model requires adequate inspection of residuals and transformations where necessary, often resulting in many costly iterations, both the expedience and practicality of which are often challenged. Finally, the use of ratios in predictive applications results in scores that are useful primarily in comparison to some selected value that is related to the objective of the analysis. Single benchmarks for comparison can lead to errors in prediction regardless of how explicitly the analysis objective is defined.

Eilon (1993), considering the framework for ratio analysis, highlights the effects of both external factors and ratio interdependence on the quality of historical and predictive analyses, noting that performance measures are not always compatible with each other, and an improvement in one measure may come at the expense of another. Such a case is exemplified by a demonstration of the relationship between the net profit margin, gross profit margin, fixed (cost-to-total) cost ratio, and the fixed cost-to-revenue proportion – if two of these ratios are known, the remaining two are automatically determined. Management control governed by strict attention to isolated performance metrics can lead to conflicting performance ratios, as is the case when the return on capital employed (ROCE) is considered as the product of the net profit margin (net profit/revenue) and the asset turnover (ATO, net sales/total assets). It can be shown that it is possible for the ROCE to increase when a decrease is seen in one of the other two ratios. When the profit margin is expressed as a function of ROCE and ATO, it can also be shown that the appropriate decreases in both the independent variables can actually produce an increase in the profit margin (Eilon, 1993).

So (1987) computed 11 financial ratios of manufacturing firms over a period of ten years, and assessed their normality by examining the skewness and kurtosis of the distributions. It was found that, even after the removal of outliers from the data, the distributions of many ratios were still non-normally and asymmetrically distributed. The most serious violations of normality were found in the cash flow-to-total debt and ROA metrics, while current assets-to-total assets and working capital-to-total assets ratios were the only ratios to have no outliers over all ten years. So concludes that the non-normal ratios are either nonlinear or that an intercept term exists in the regression of one variable on the other variable comprising the ratio, and the offset is the result of influences on the dependent variable that are not related to the independent variable.

Numerous techniques have been employed to provide insight into the normality of financial data. The mean, median, standard deviation, and variance provide an indication of the central tendency and dispersion of the distribution. Skewness and kurtosis are used to assess the tailing and flatness of the distribution, respectively, while many test statistics for normality have been devised. The chi-square (χ^2) goodness-of-fit test divides the range into a number of equally probable classes and compares the number in each class to the number expected. For the test to be meaningful, it is generally thought that a minimum sample size of 30 is required. The Shapiro-Wilk test has been shown to be an effective test for normality, even for sample sizes of less than twenty (Shapiro and Wilk, 1968). It is based upon comparing the quantiles of the fitted normal distribution to the quantiles of the data, is especially sensitive to asymmetry, tails and outliers, and is more sensitive to non-normality than the Kolmogorov-Smirnov test, rejecting the normality assumption more often. Positive skewness in raw financial ratios has been consistently demonstrated in numerous industries. Various transformations have been shown to reduce skewness in some cases, while deteriorating test statistics in others. For example, the natural log transformation has been shown to outperform the square root transformation, decreasing the ability to reject normality at both 1% and 5% levels of significance (Ezzamel et al., 1987).

J.-P. Kallunki et al. (1996) examined the proportionality of financial ratios, including return on investment (ROI), return on equity (ROE), current ratio and quick ratio, among others. Because of the heteroscedasticity of regression models of ratio outputs on their respective inputs, transformation to more homoscedastic models was performed, and the resulting coefficients were tested for proportionality. Deviations from proportionality were found in 10% of the cases. From their results they conclude that, from a proportionality standpoint, the use of ratios is valid in financial statement analysis, but care should be taken to assess normality prior to using ratios for decision making.

Data Envelopment Analysis

Operating units of organizations, as well as organizations within a larger genre, have multiple inputs and outputs, creating difficulty in determining which units are efficient in converting their inputs to outputs. Data envelopment analysis (DEA) is an application of linear programming that allows measurement of the relative efficiency of specific organizations, business units or firms (referred to as decision making units, or DMUs) against a composite efficient frontier composed of measures that are common to all the units. Charnes et al. (1978) applied the linear programming technique to the efficiency of systems composed of multiple inputs and outputs, first proposed by Farrell (1957) and Farrell and Fieldhouse (1962). Using the notation of Smith (1990), the model determines the set of weights, $\boldsymbol{\lambda} = (\lambda_1, \lambda_2,..., \lambda_n)^r$, and the extent to which firm 0 can reduce all its inputs, h_0, when the vector of inputs , $\mathbf{x}_j = (x_{1j}, x_{2j},..., x_{mj})^r$, and the vector of outputs, $\mathbf{y}_j = (y_{1j}, y_{2j},..., y_{sj})^r$, are known for each firm j, $j = 1,..., n$, for n firms under consideration using m inputs and producing s outputs. For firm 0, then, the linear program, referred to as the CCR model, can be written

$$\text{minimize} \quad h_0$$

$$\text{subject to} \sum_{j=1}^{n} x_{ij} \cong \lambda_j \# h_0 \cong x_{io} \quad i = 1,2,\ldots, m$$

$$\sum_{j=1}^{n} y_{rj} \cong \lambda_j \exists y_{r0} \quad r = 1,2,..., s$$

$$h_0, \lambda_j \exists 0 \quad j = 1,2,..., n$$

The CCR model assumes constant returns to scale for both the inputs and outputs. Banker, Charnes and Cooper (1984), to address the case of variable returns to scale, introduced an additional constraint, that of the summation of the weights, λ, being set equal to unity, written as

$$3\ \lambda_{\mathbf{j}} = 1$$

Variable returns to scale are desirable, as managers have little or no ability to affect the returns to scale within one year. Also, where there is no knowledge of the nature of the effect of scale performance, the BCC model is more flexible in accommodating inter-industry differences.

The dual of the above linear program may be used to show that the solution is equivalent to finding the vectors of the output weights, $\mathbf{u} = (u_1,..., u_s)^r$ and input weights $\mathbf{v} = (v_1,..., v_s)^r$ that maximize the ratio

$$h_0 = 3\, u_r y_{r0} \ni 3\, v_i x_{i0}$$
$$\text{r = 1 i = 1}$$

subject to $\sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij} \leq 1$ for all $j = 1,..., n$,

and u_r, $v_i > 0$ for all $i = 1,..., m$ and $r = 1,..., s$. Thus, DEA searches for the input and output weights that maximize the performance of the firm being analyzed, while conventional ratio analysis imposes values on these vectors based on historical information (Smith, 1990).

For example, if the input is inventory and the output is net sales, the DEA model finds the best value of inventory turnover among the firms being investigated, and this efficient firm will exhibit $h_0 = 1$. Less efficient firms will have values of h_0 less than unity. The value of h_0 becomes, for a given inefficient firm, the relative efficiency at which sales are generated using inventory.

Examination of the BCC model reveals features that are beneficial in lieu of other conventional financial analysis techniques. First, as pointed out by Charnes and Cooper (1985, p. 74), DEA uses multiple input and output variables to generate h_0, a measure of overall financial performance. Thus, DEA provides a solution to the shortcoming of neglected interdependence of performance variables in conventional ratio analysis by incorporating several financial metrics into a single measure. The ability to simultaneously evaluate multiple inputs and outputs allows a composite financial performance ratio for subsequent statistical analyses.

Second, DEA provides the estimated efficient frontier, derived from the best performing firms (Charnes and Cooper, 1985, p. 60), for subsequent comparison of the other firms – no reference value or industry norm is required, nor is an externally generated performance model to which the variables must be fitted. The performance of the efficient firms, then, is meaningful, as such performance is relative to the less efficient firms. Therefore, the benchmark firms provide a realistic, attainable, superior level of operation. Another advantage to the variable weightings being generated without an externally specified function is that each firm has its own optimum function that results in its being evaluated in the best possible light. Therefore, the technique is flexible such that evaluation of each DMU is executed using a uniquely optimum model, highlighting the variables from which optimality is derived, yet not ignoring the remaining financial and operational variables.

Finally, to avoid complex arrays of ratios, the use of traditional financial ratios to assess the financial or operational performance of firms would require the development of an index number that would provide a single summary number for such activities as statistical analysis and performance ranking. Development of an index number would require selection of a priori weights to reflect the relative importance of each element included in the index number (Banker et al., 1989, p. 128). Difficulties that may be encountered in assigning these weights are bypassed by DEA because the latter does not require a priori weight selections in order to arrive at its overall performance evaluations. The weights assigned by the DEA model to the organization and its variables that are under evaluation are obtained from the data as part of the solution to the mathematical programming problem used to determine efficiency (Banker et al., 1989, p. 128).

DEA determines the relative efficiency of a group of organizations in two steps. Based upon the selected inputs and outputs of the firms being studied, the efficient frontier is found, according to one of two general model formulations. That is, the efficient frontier is based on either the maximized outputs for a given level of inputs or the minimized inputs for a given level of output. This study utilizes the latter formulation. The researcher also specifies the approach to scale factors, selecting the assumption of either constant or variable returns to scale (the assumption adopted for this study). The second step entails the calculation of efficiency scores for the DMUs in the model. For the input minimization model, the model output is used to determine the levels to which all inputs must fall to bring each firm to the efficient frontier. The proportion of the actual input quantity occupied by the target input quantity produces the efficiency score. Thus, a firm on the efficient frontier needs no decrease in inputs to remain there, and therefore, the efficient DMUs are given a score of one. It should be emphasized that efficient firms are only efficient relative to the peer firms included in the analysis. DEA provides no insight into the degree to which efficient firms may improve their performance.

Data and Analyses

A total of 18 firms from seven different three-digit SIC codes was selected for analysis. The companies were part of a larger group of companies that had supplied information on lean systems adoption via a survey completed by the appropriate operational and financial managers. Selection was performed such that all the lean implementation dates were within a five year period to impart homogeneity of the external environment. The overall time frame was selected based on the availability and completeness of financial statement data. The distribution of companies in the SIC codes, along with the dates of lean system adoption, are listed in Table 1.

Table 1

Selection Information for Studied Firms

IC Code	SIC Description	Number of Firms	LEAN Adoption Date Range
356	General Industrial Machinery & Equipment	2	1993-1994
357	Computer and Office Equipment	6	1991-1995
366	Communications Equipment	1	1994
367	Electronic Components and Accessories	1	1993
371	Motor Vehicles and Motor Vehicle Equipment	3	1993
382	Laboratory Apparatus and Analytical	4	1993-1995
386	Photographic Equipment and Supplies	1	1994

To examine the effects of lean systems implementation on the financial performance of the firms, financial data was obtained for the two years preceding the adoption date, for the actual year of adoption, and for three years after implementation. Because any performance enhancements resulting from lean manufacturing implementation would be discerned relative to the most efficient firms, assessment was not performed year-over-year. Rather, the data set was prepared by placing the metrics from balance sheets, income statements and statements of cash flow, for all the years of interest, into a single source file. The combinations of firms and financial years were coded such that the DEA procedure could construct the efficient frontier and produce the efficiency scores from firm-years in the entire six-year range. For a given combination of financial inputs and outputs studied, results were obtained in the form of ranked efficiency scores from the best performance to the worst in the six relative years of lean systems adoption. The scores were then sorted by year to test the pre- versus post-adoption null hypothesis, namely,

$H_{0,1}$: There is no statistically significant difference in financial performance of firms before and after implementation of lean systems, as determined by DEA performance measures.

The work of Fernandez-Castro and Smith (1994) focused on the use of ratios taken directly from the financial statements of companies obtained from the EXSTAT data base, and the financial data was input into the DEA procedure in ratio form. While this study utilizes corporate financial statements as the source of data, the form of the financial information used is simply the actual financial metric as obtained from the source statement. This approach was used by Bowlin (1999) in his comparison of US defense and non-defense manufacturers.

The DEA portion of the study was executed in two parts. First, models were generated to assess trends in the use of labor and inventory to produce revenue and income. Boyd et al. (2002) determined, regressing traditional ratios a similar period of time, that inventory turnover and labor utilization were benefactors of lean implementation. However, they were unable to resolve similar effects regarding the effect of lean manufacturing system implementation on profit measures. Therefore, it is of interest to examine the effect of lean system implementation on DEA outputs taken as the income statement is descended. The DEA model, using net sales as the output with inventory and labor (number of employees) as the inputs, was supplemented by similar models generated with identical inputs and gross profit; earnings before interest, taxes, depreciation and amortization (EBITDA); earnings before taxes (EBT); and net income, taken sequentially as the outputs. For each model, the mean efficiency scores, including those of the efficient firms, were calculated for each relative year of adoption in order to discern trends resulting from implementation of lean systems. It should be noted that negative values were encountered in the EBT and cash flow metrics. Because negative values are disallowed in data envelopment analysis, all values were adjusted upward by a constant sufficient to make the lowest value slightly positive. Statistically significant changes in the DEA efficiency scores due to lean implementation for each of the income statement outputs were assessed using the statistical test presented by Banker (1989, 1993), and utilized by Bowlin (1999). Banker (1989, pp. 236-237; 1993, pp. 1271-1272) suggests a form of an F-test to measure the variance of the reciprocal of the DEA efficiency score, $1 \ni h_0$. Assuming that $1 \ni h_0$ is exponentially distributed, the test statistic is (Banker, 1989, p. 236)

$$\left[\sum_{i=X_t}(1/h_{ipost}-1)/n_2\right] \Big/ \left[\sum_{i=X_t}(1/h_{ipre}-1)/n_1\right],$$

where h_{ipre} and h_{ipost} are the financial performance measures computed from the DEA model for the years preceding and following adoption of lean manufacturing, respectively, and n_1 and n_2 are the number of scores in the pre-adoption and post-adoption samples, respectively. The test statistic follows the F-distribution with $2n_1$ and $2n_2$ degrees of freedom (Banker, 1989, p. 236; 1993, p. 1272).

The values in the denominator of the test statistic are exclusively from the two years preceding the year in which lean systems were implemented. However, two instances of the significance test were performed, with the numerator for the first instance using efficiency scores from all three years after implementation, and the numerator in the second instance using values from only the second and third years after implementation. The second instance was performed without the post-adoption first year to investigate the one-year time delay in the detection of productivity gains resulting from JIT implementation, as reported by Lieberman and Demeester (1999), noting lags in the time structure associated with the coefficients of Granger causality tests. The test statistic was used to determine the probability of rejecting the hypotheses regarding the statistical significance of the differences detected between pre- and post-adoption efficiencies.

In the second portion of the study, DEA models were constructed to assess the efficiency of the firms in generating three outputs, operating profit (EBITDA), operating cash flow, and net sales, from three inputs, inventory, number of employees, and "other assets", defined as total assets less inventory. A DEA model constructed in this fashion incorporates the inputs and outputs used in calculating cash return on assets (CROA, operating cash/total assets), asset turnover (ATO, net sales/total assets), labor utilization (net sales/number of employees), inventory turnover (ITO, net sales/average inventory), and the return on assets using operating profit. Banker's test statistic (Banker, 1989, pp. 236-237; 1993, pp. 1271-1272) was again employed, with this more elaborate model, to determine the statistical significance of the improvement in efficiency scores after adoption of lean manufacturing as compared to pre-adoption values. As with the income statement outputs, the test statistic was calculated using the format noted above, with both pre-adoption years taken into consideration, and the two scenarios, involving all three post-adoption years followed by years two and three only. Table 2 summarizes the DEA inputs and outputs for all of the models generated.

Additionally, the actual ratios, constructed from the metrics supplied to this model, were calculated and trended over the relative lean adoption time frame to compare the implications of the DEA results with the conventional ratios. The characteristics of the distributions of both the DEA performance measures and corresponding financial ratios, taken from year to year, with regard to the degree of normality, are also compared. Specifically, the Shapiro-Wilk (1968) test was employed, along with comparison of the standardized skewness and kurtosis values for the distributions, to test the second and third null hypotheses, stated as follows:

$H_{0,2}$: The selected conventional financial ratios of the firms are from normally distributed populations.

and, similarly,

$H_{0,3}$: The DEA performance measures of the firms are from normally distributed populations.

As noted in the analysis of income statement outputs, negative values were also encountered in the operating cash flow data, and were adjusted in similar fashion, with sufficient offset to make the lowest value slightly positive.

Table 2

Summary Listing of DEA Models Constructed to Evaluate LEAN/JIT Effects

Inputs	Outputs
Inventory number of employees	net sales
Inventory number of employees	gross profit
Inventory number of employees	EBITDA
Inventory number of employees	EBT
Inventory number of employees	net income
Inventory number of employees all other assets	net sales operating profit operating cash flow

Results and Discussion

The results are developed to provide insight into three concepts. First, it is important to determine the effects, if any, of lean manufacturing/JIT implementation on the financial performance of the manufacturing firms studied (hypothesis $H_{0,1}$). Second is an assessment of the ability to elucidate such effects, providing estimates of statistical significance, from standard corporate financial statements using data envelopment analysis. The third concept embodies the normality of the distributions of conventional financial ratio data as compared to the distributions of performance scores resulting from DEA models (hypotheses $H_{0,2}$ and $H_{0,3}$).

Figure 1 shows the DEA performance score trends exhibited by each successive measure of financial inflows taken from the income statements of the studied firms, including net sales, gross profit, EBITDA, EBT, and net income. Recall that the income statement outputs were modeled with inventory and number of employees chosen as the inputs. Note that, as the income statement is ascended, from net income to net sales, the trends take on a more positive slope, with apparent increases in efficiency in the years after lean adoption (relative adoption year = 0).

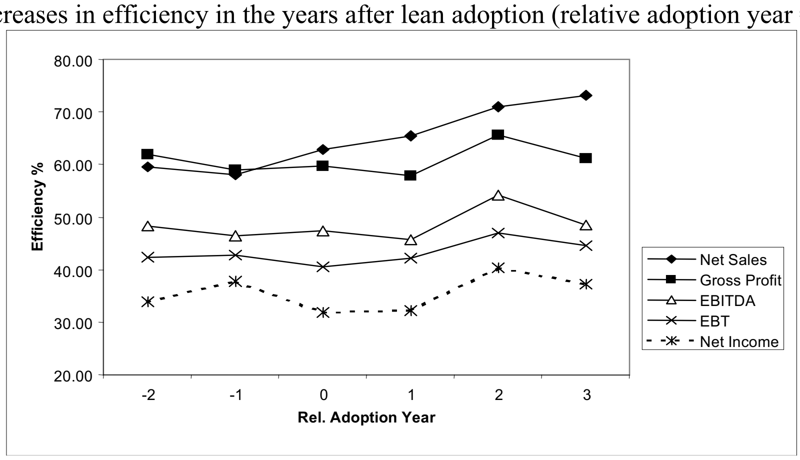

Fig. 1. Mean DEA performance measures for the income statement outputs by relative year of LEAN adoption

Furthermore, as charges against revenue are developed down the income statement, the efficiency scores decline. The largest decrease occurs with the accounting for sales, general and administrative expenses and research and development charges, resulting in the values for EBITDA. The Banker (1989, 1993) test statistic was calculated using the DEA performance ratings for each income statement output. The ratio values are listed in Table 3, along with the probabilities associated with the acceptance of the null hypothesis that, for each output type, there is no statistically significant difference between the efficiencies before and after lean systems implementation. As indicated in Table 3, the significance testing was performed for a comparison of the two years prior to JIT adoption with the three years after adoption, as well as the two years before versus the second and third years post-adoption. In every case, the ratio was less than unity, which, because the post-adoption data was placed in the numerator, indicates higher performance scores were obtained in the years after lean systems implementation. It is also noted that the post-adoption years exhibit improved performance, with the differences being statistically significant at over 90% confidence for all efficiencies except those resulting from the gross profit output model. Thus, the null hypothesis, ($H_{0,1}$) is rejected for the net sales, EBITDA, EBT and net income measures. Such results indicate an improvement in measures taken from nearer the bottom line as compared to the results obtained by Boyd et al. (2002) and Balakrishnan et al. (1996), who were unable to readily discern positive effects on all profit-related metrics. However, these results are more in keeping with those obtained by Kinney and Wempe (2002), who were able to show statistically significant increases in ROA, with the major boost coming from the profit line. Comparing the probabilities obtained with and without the first year after implementation of lean manufacturing systems, it is apparent that there may be a one-year lag in the appearance of the expected benefits, as discussed by Lieberman and Demeester (1999). Figure 2 depicts the mean DEA performance score trend obtained for the model generated with net sales, operating profit, and operating cash flow outputs, using inventory, number of employees, and all other assets as inputs. The upward trend is more pronounced than that exhibited by the income statement models with regard to lean systems improvement effects after the relative adoption year. Significance testing using the test statistic proposed by Banker (1989, 1993) resulted in a ratio value of 0.435 for the comparison of the three post-adoption years to the two pre-adoption years, with the associated probability of null hypothesis acceptance being less than 0.0001. It is obvious, but not meaningful, that a ratio value of 0.263, calculated for the comparison of post-adoption years 2 and 3 to the two pre-adoption years, further reduces the probability of accepting the null hypothesis. The one-year time lag for the manifestation of lean manufacturing improvements in the financial statements is not obviated by the DEA model developed using more inputs and outputs. Improvement comes in the first year after implementation, and further improves in the following year. Thus, combining the outputs allows the stronger effect of net sales improvement to influence the model such that the trend takes on the appearance of the net sales line in Figure 1. Verification is provided by the relative contributions of the outputs to the DEA model, as the contributions of net sales, operating income and operating cash flow are 55.8%, 32.6% and 11.6%, respectively.

Table 3

Values of the DEA exponential test statistic and two-tailed probabilities for income statement-derived performance measures

	Years -2, -1 vs. 1, 2 and 3		Years -2, -1 vs. 2 and 3	
Parameter	Ratio	Prob.	Ratio	Prob.
Net Sales	0.607	0.0092	0.554	0.0065
Gross Profit	0.834	0.1943	0.803	0.1764
EBITDA	0.673	0.0310	0.319	< 0.0001
EBT	0.632	0.0153	0.380	< 0.0001
Net Income	0.758	0.0959	0.563	0.0080

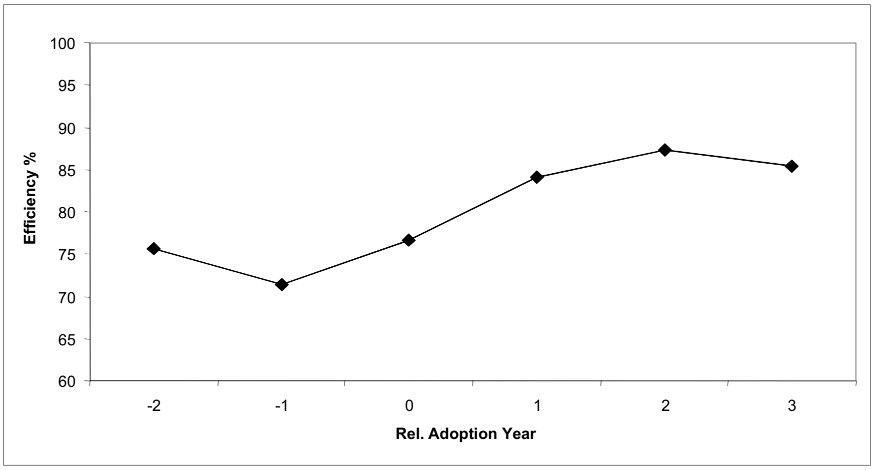

Fig. 2. Average performance score trend for the combined output model (net sales, operating profit, and operating cash flow)

One of the cautions associated with data envelopment analysis that is made clear to its users, as models are further refined, is that the number of efficient firms increases readily upon subsequent addition of input variables. The number of efficient firms in this study grew from an average of 6.4 for the individual income statement models to a total of 29 for the more developed model containing three outputs and three inputs. Therefore, the researcher's ability to impart greater significance to effects such as those resulting from lean implementation is based upon the variables chosen and their relative contributions, not upon the absolute number of variables incorporated into the model.

Plots of the mean values of conventional financial ratios that are associated with the inputs and outputs used in the more highly developed DEA model over the relative lean systems adoption years are depicted in Figure 3. Note that the trends of ratios that contain net sales in their numerators are positive, while the ratios containing net income and cash flow do not exhibit such positive trends. Optimized t-statistics to evaluate the differences in mean ROA and CROA were 0.334 and 0.370, respectively, with corresponding probabilities of a statistically significant difference being 0.740 and 0.713, respectively. Thus, conclusions regarding the effects of lean manufacturing on firm performance would vary with the selective incorporation of financial measures into univariate or multivariate statistical treatments. In general, the results of strategic initiatives, assessed using multiple financial ratios, are dependent upon the weight with which each financial metric influences the output of the evaluation technique, as well as which metrics are used. Using the financial data for the firms included in this study in the form of ratio measures, one would conclude that an increase in asset turnover and the lack of a positive trend for the ROA metric implies a negative overall effect on net income. As shown in Table 3, such is not the case, especially when a one-year lag in implementation effects is considered. Therefore, the tendency to combine multiple conclusions from individual ratios based on assumed relationships between the measures can lead to suspect conclusions. Furthermore, the use of ratios to assess statistically significant effects such as those listed in Table 3 is also dependent upon their being normally distributed, an assumption that can be as suspect as the tendency to reach combined conclusions from individual financial measures.

The distributions of the ratios shown in Figure 3 were characterized with respect to their normality, by year of adoption, as were the corresponding DEA performance scores. Specifically, the Shapiro-Wilk test was used, in addition to standardized skewness and kurtosis values, to obtain probability estimates for acceptance or rejection of null hypotheses, $H_{0,2}$ and $H_{0,3}$, that is, that the financial measures are taken from normally distributed data. The results are presented in Table 4.

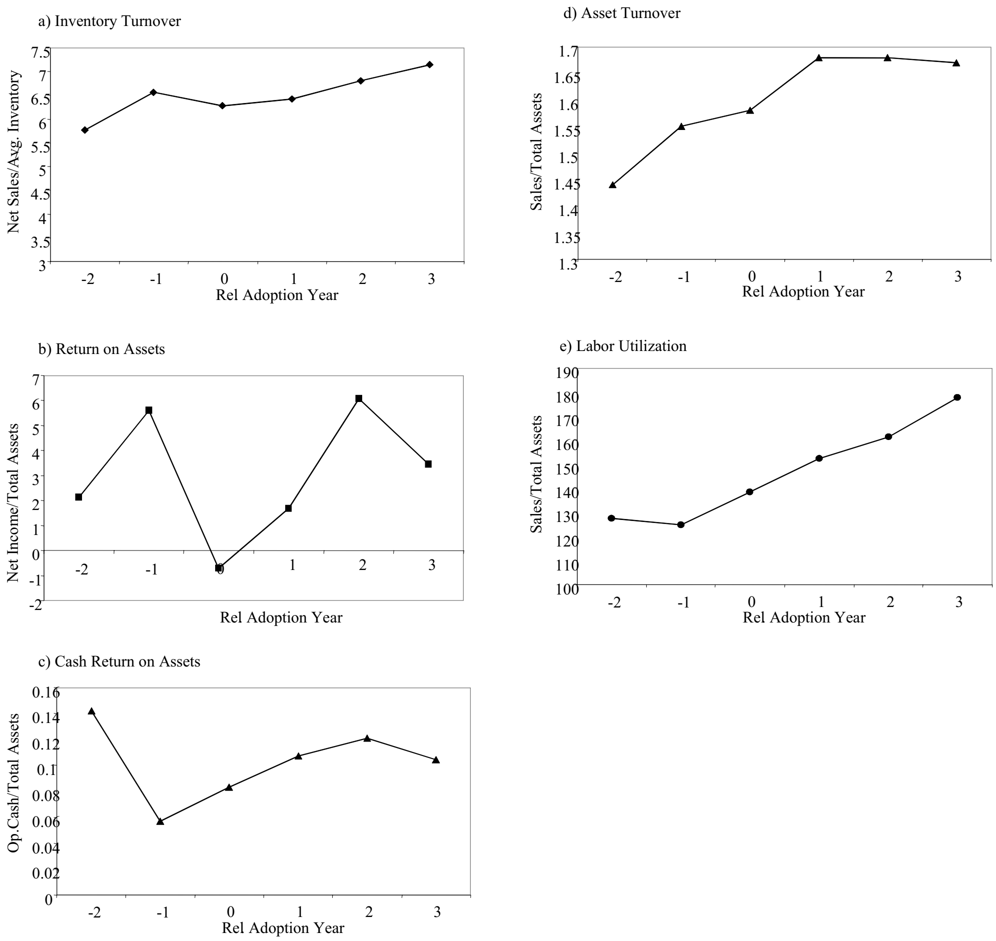

Fig. 3. Mean values of conventional financial ratios over the relative adoption years studied

Because the DEA procedure requires the establishment of efficient units and the assignment of scores of 100 to the efficient units, these scores were omitted from the distribution characterization to avoid assured skewness. Note that the inefficient units' DEA scores are normally distributed throughout all six relative adoption years, per the three normality parameters calculated. In more than 55% of the tests performed on the conventional ratios, the assignment of normality is rejected. Thus, the null hypothesis, $H_{0,2}$, is rejected for the DEA efficiency scores, while $H_{0,3}$ is accepted for the DEA performance measures. Non-normal skewness values indicate tailing to the high side, with sufficient tailing, in the case of inventory turnover data, to affect higher kurtosis values. Furthermore, all of the inventory turnover values are deemed non-normal, and longitudinal examination of the results indicates there is no apparent relationship between the relative adoption year and the distributional characteristics.

Table 4

Results of Shapiro-Wilk tests

Distribution Parameter	Rel. Adoption Year	Asset Turnover	Return on Assets	Inventory Turnover	Labor Utilization	Cash Return on Assets	DEA Score
Shapiro-Wilk (p-value)	-2	0.953 (0.475)	0.938 (0.273)	**0.618 (< 0.001)**	0.899 (0.054)	**0.627 (< 0.001)**	0.968 (0.806)
	-1	**0.775 (< 0.001)**	0.929 (0.188)	**0.428 (< 0.001)**	**0.834 (0.004)**	**0.863 (0.012)**	0.968 (0.785)
	0	**0.873 (0.019)**	**0.646 (< 0.001)**	**0.618 (< 0.001)**	**0.848 (0.007)**	0.980 (0.937)	0.950 (0.474)
	1	**0.879 (0.024)**	**0.775 (< 0.001)**	**0.622 (< 0.001)**	**0.917 (0.115)**	0.955 (0.499)	0.902 (0.162)
	2	**0.804 (0.001)**	0.897 (0.051)	**0.712 (< 0.001)**	0.930 (0.199)	0.974 (0.855)	0.987 (0.990)
	3	**0.896 (0.049)**	**0.830 (0.005)**	**0.730 (< 0.001)**	**0.891 (0.040)**	0.917 (0.117)	0.914 (0.200)
Standardized Skewness (p-value)	-2	0.779 (0.435)	0.893 (0.372)	**3.083 (0.002)**	1.480 (0.139)	**3.129 (0.002)**	0.417 (0.677)
	-1	**2.554 (0.011)**	0.986 (0.324)	**3.530 (< 0.001)**	**2.170 (0.030)**	1.912 (0.056)	0.505 (0.614)
	0	1.916 (0.055)	**3.090 (0.002)**	**3.109 (0.002)**	1.862 (0.063)	0.408 (0.683)	0.124 (0.901)
	1	1.459 (0.145)	**2.324 (0.020)**	**3.042 (0.002)**	1.351 (0.177)	0.162 (0.871)	0.902 (0.162)
	2	**2.028 (0.043)**	1.450 (0.147)	**2.531 (0.011)**	0.965 (0.335)	0.284 (0.777)	0.336 (0.737)
	3	1.390 (0.165)	**2.143 (0.032)**	**2.344 (0.019)**	1.641 (0.101)	1.101 (0.271)	0.421 (0.673)
Standardized Kurtosis (p-value)	-2	-0.390 (0.696)	1.582 (0.113)	**3.922 (< 0.001)**	**2.332 (0.020)**	**4.069 (< 0.001)**	-0.199 (0.842)
	-1	**3.271 (0.001)**	-0.008 (0.994)	**4.471 (< 0.001)**	**3.120 (0.001)**	**2.748 (0.006)**	0.554 (0.579)
	0	**2.346 (0.019)**	**4.006 (< 0.001)**	**3.975 (< 0.001)**	**2.764 (0.006)**	0.169 (0.866)	-0.661 (0.509)
	1	1.220 (0.222)	**2.659 (0.008)**	**3.861 (< 0.001)**	1.397 (0.163)	1.492 (0.136)	-1.793 (0.073)
	2	**2.120 (0.034)**	1.496 (0.135)	**3.021 (0.003)**	1.442 (0.149)	0.096 (0.923)	0.058 (0.954)
	3	0.876 (0.381)	**2.659 (0.008)**	**2.532 (0.011)**	**2.348 (0.019)**	0.750 (0.453)	-1.297 (0.195)

Standardized skewness and standardized kurtosis values for selected financial ratios and DEA performance scores (for three-output model). Emboldened values indicate rejection of the null hypothesis (∃ 95% conf.) that the sample population is normally distributed.

Conclusions

Based on the empirical evidence presented, it is concluded that data envelopment analysis can be used to evaluate the performance of for-profit firms in producing various financial outputs, simultaneously, as a function of chosen inputs, and such evaluations may be used in lieu of, or to supplement, conventional ratio analysis. In this study, DEA was used to assess improvements in the efficiency with which companies use inventories and labor to produce sales, as a result of the implementation of lean manufacturing systems.

DEA was also employed in determining similar improvements in the efficiency with which selected manufacturing firms use inventories, labor and all other assets to produce sales, operating income, and operating cash flow. Using an appropriate means of determining statistically significant changes in DEA efficiency measures, this study showed, for the manufacturing firms used, that the implementation of lean manufacturing systems improves output of financial production, with notable improvements coming in terms of net sales, operating income (earnings before interest, taxes, depreciation and amortization), earnings before taxes, and net income. Differences in the income statement DEA performance measures with and without efficiencies assigned to the first year after lean system implementation indicate that the time lag seen in previous studies (Lieberman and Demeester, 1999) is not necessarily the result of the metrics chosen or the statistical methods used. No time lag was demonstrated by the more descriptive model incorporating sales, operating income and operating cash into a single efficiency measure, as statistical comparisons with and without the first post-adoption year both result in probability statements that lead convincingly to rejection of the null hypothesis that pre- and post-adoption performance is identical. It is concluded that the DEA modeling methodology is adequate for assessment of even more descriptive scenarios, i.e., using more inputs and outputs, as long as the researcher realizes that incorporation of more variables ultimately hinders the resolution of efficiency with regard to the DMUs being studied.

Conventional financial ratios, such as the return on assets (ROA), inventory turnover (ITO), asset turnover (ATO), labor utilization (LU), and cash return on assets (CROA), were calculated for the relative adoption years parallel to the years investigated using DEA. The trends exhibited by the sales-related ratios (ITO, ATO, and LU) confirmed the positive effects of lean manufacturing systems determined by the DEA models. However, both graphical and statistical analyses of the two ratios more dependent on generation of income, CROA and ROA, unlike the DEA performance measures that incorporated the same inputs and outputs, were inconclusive in the elucidation of JIT effects.

Finally, suitability of some of the conventional financial ratios constructed from the financial statement data used in this study is in question with regard to the assumption of univariate normality. The majority (over 55%) of the ratio distributions, tested for each relative adoption year, were shown to be non-normal using the Shapiro-Wilk (1968) test, standardized skewness, and standardized kurtosis values. The lack of normality for the distributions of such commonly used ratios calls for scrutiny in their application to statistical techniques that require normally distributed data. It also appears to be more expedient to evaluate the normality of DEA efficiency measures once the desired model has been generated, as compared to the laborious scrutiny of multiple inputs to a less robust statistical method.

Because of the limited number of documented studies that apply data envelopment analysis to corporate, for-profit, and, particularly, manufacturing DMUs, relative to those focused on service and public-sector entities, it is clear that more extensive examination of models constructed from financial statements is warranted. Exposition of a plethora of statistical models has led to the knowledge of what independent variables impact a number of desired responses. Similar development of additional appropriate input and output combinations for DEA analysis, to supplement the current, well-documented routine analyses, constitutes one of a number of plausible avenues for further study.

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